

Predicting User Experiences through Cross-Context Reasoning

Shlomo Berkovsky¹, Lora Aroyo², Dominik Heckmann³, Geert-Jan Houben⁴,
Alexander Kröner³, Tsvi Kuflik¹, Francesco Ricci⁵

¹University of Haifa, Israel
{slavax@cs, tsvikak@is}.haifa.ac.il

²Technical University of Eindhoven, The Netherlands
l.m.aroyotue.nl

³German Research Center for Artificial Intelligence
{heckmann,kroener}@dfki.de

⁴Vrije Universiteit Brussel, Belgium
Geert-Jan.Houben@vub.ac.be

⁵Free University of Bolzano/Bozen, Italy
fricci@unibz.it

Abstract

The existing personalization systems typically base their services on general user models that ignore the issue of context-awareness. This position paper focuses on developing mechanisms for cross-context reasoning of the user models, which can be applied for the context-aware personalization. The reasoning augments the sparse user models by inferring the missing information from other contextual conditions. Thus, it upgrades the existing personalization systems and facilitates provision of accurate context-aware services.

1 Introduction

The overwhelming size of nowadays information world, jointly with limited processing capabilities of the users pose a need for developing and exploiting personalization approaches allowing an easier navigation and access means. Personalization research yielded a number of techniques, such as collaborative [Herlocker et al., 1999] and content-based filtering [Morita and Shinoda, 1994], item-to-item collaborative filtering and others. These techniques facilitate adapting the services provided to the user to his/her actual interests and needs, as expressed by the User Models (UMs) [Kobsa, 2001] that constitute an essential input for every personalization technique.

Despite an intensive research, aimed mainly at improving the prediction accuracy of the personalized recommendations provided to the user, personalization techniques suffer from a severe limitation. The provided personalization typically relies on a UM, which has been tailored for an application, characterized by specific personalization algorithms and a specific application domain. Moreover, user needs represented in the UM are generally

valid only in a specific context, which is typically ignored by the state-of-the-art personalization systems.

Taking into account various contextual conditions may be beneficial and even essential for providing accurate and efficient personalization. For example, consider an everyday task of recommending radio music for a user during his/her daily driving from home to work. Although the user's music preferences are quite steady, different types of music may be recommended as a function of his/her mood, presence of other people, traffic conditions and even weather conditions. Hence, there is an emergent need for *slicing* the general preferences represented by the UM according to various contextual conditions. This will allow considering the contextual aspects and providing the user context-aware personalization.

On one hand, providing the user context-aware personalization may significantly improve the accuracy and the usefulness of the provided personalization service. On the other hand, the information stored in the UMs may not suffice for providing accurate context-aware personalization. This will happen due to the above slicing of the general UMs that will split the available information about the user according to the appropriate contextual conditions. Hence, any attempt of inserting the context-awareness dimension into the state-of-the-art personalization systems should involve developing a reasoning mechanism, which will facilitate inferring the essential parts of the UMs across various contextual conditions.

This position paper focuses on developing mechanisms for cross-context reasoning of the UMs, which can be applied for the purposes of the following context-aware personalization. The core element of these mechanisms is referred to as *user experience*, or for the sake of brevity, just *experience*. By experience we denote an explicit or implicit feedback provided by a user as a result of experiencing a certain content (or item) in a certain context. Figure 1 schematically illustrates the experience compo-

nents. For example, a user John Doe may rate pop-music radio program listened when driving alone on a rainy morning by assigning it 4 stars on a 5-stars scale. In this case, the experience of 4 stars is given by the user John Doe to the content of pop-music radio program in the context of a rainy weather and being alone. The union of such experiences is considered as the UM. Given a set of past experiences represented by the UM, the goal of the above cross-context reasoning mechanism is inferring the essential parts of the UM for the purposes of generating accurate context-aware personalization for future experiences.

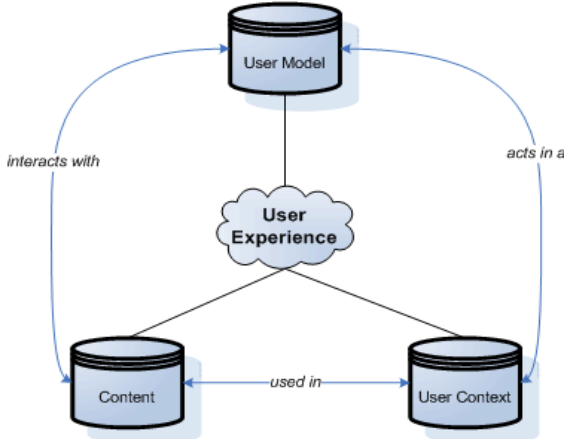


Figure 1: Representation of User Experiences

Our approach is based on semantically-enriched descriptions of the experiences. This means that all the components affecting the experience, i.e., users, contents and contexts, are described using semantic schemata. These schemata facilitate defining various cross-context reasoning mechanisms, which will augment the sparse parts of the UM by inferring the missing information from past experiences in other contextual conditions.

Moreover, cross-context reasoning may be integrated with other personalization approaches, such as cross-user (i.e., collaborative) and cross-content (i.e., content-to-content, or item-to-item) reasoning. For example, applying the reasoning mechanisms on the experiences of similar users on the required content will lead to collaborative cross-context reasoning, while applying them on the experiences of the given user on similar contents will lead to item-to-item cross-context reasoning. Also, we consider applying an advanced cross-context hybrid reasoning, integrating both cross-user and cross-content reasoning.

Hence, the contribution of our work is two-fold. First, we provide a high-level framework for semantic representation of context-aware user experiences on contents. Second, we exploit this framework for defining various reasoning mechanisms for (1) inferring the essential parts of context-aware UMs, and (2) providing context-aware personalization. This upgrades the capabilities of the state-of-the-art personalization systems and facilitates provision of accurate context-aware personalization services.

The rest of the paper is structured as follows. In section 2 we overview the related works on semantic-based and context-aware personalization approaches. In section 3 we briefly describe an example scenario that will be used for the following semantic representation and reasoning. In section 4 we discuss the semantic data representation. In section 5 we discuss the proposed reasoning mechanisms. Finally, in section 6 we conclude the paper and discuss several veins for future research.

2 Related Work

Rich context models are of special value for user support outside of a typical desktop scenario. For instance, when guiding its user through a museum or during a sight-seeing tour, an assistant may adapt its personalization with respect to contextual information such as the visitor's interests, location, available time, financial limitations, mobility constraints, and local weather conditions (see, for instance, [Davies et al., 2001] and [Cinotti et al., 2004]). Here, the user stays in variations of a single context (the tour); other scenarios combine such rich context models with adaptation to diverse tasks. For instance, [Kuwahara et al., 2003] describe a context-aware assistant, which aims at avoiding nursing accidents in hospitals. The system has to distinguish between diverse context models of various nursing tasks and has to predict actions before their actual occurrence. This approach includes modeling across contexts in various dimensions; however, even in this case the set of supported contexts is of limited size and is known in advance.

The previously described works make use of UMs, which provide information about the user in diverse contexts. Such contextualized user modeling is a research area on its own. As pointed out in works such as [Harvel et al., 2004] and [Kern et al., 2006], context-based user modeling may already be performed on the level of sensor data. Our work aims at a higher level of abstraction, in particular, at a UM built from semantic structures. An instance of this approach is provided by [Mehta et al., 2005], who propose the use of a common ontology-based user-context model as a basis for the exchange of UMs across applications. In their approach the context is modeled as an extensible set of facets representing the characteristics of the user and his current context. Ubiquitous user modeling [Heckmann, 2005] extends this idea by continuously modeling the user by means of situational statements, which enables modeling of the user in (ideally) any context. However, if the user is in a context not experienced before, the question arises which information from previous contexts could be exploited for user support. Therefore, we propose in this article a reasoning mechanism which allows for assembling a UM for a given situation based on previous experiences.

The use of context for adapting user support is subject of considerable research efforts in recommender systems research. For instance, [Herlocker and Konstan, 2001] presents a task-focused recommender, which first retrieves items similar to items associated with some task, and then applies collaborative filtering in order to rank the items based on the interest prediction. In this case, context is defined by the task only. [Adomavicius et al., 2005] discusses the ways for achieving a more complex context model for recommendations by means of a multi-dimensional data warehousing approach. However, while the latter allows providing context-aware recommendations, it does not deal with projecting user modeling information between various contextual conditions.

In [Ricci et al., 2003] a case-based recommendation approach has been used to model a travel recommendation session as a case. Here, a case is indexed by various contextual features, such as the type of travel, the group composition, the distance from the target location, the travel season and so on. These features, among others, contribute to determining what stored recommendation sessions must be retrieved to influence the ranking of the items

considered by the user. Hence, similarity-based reasoning is exploited to make cross-context deductions.

3 Example Scenario

Everyday life is composed of various events where users request and use information. This information should suit the individual characteristics of the users and the specific context of that user. As an example, let us consider two days that contain simple traveling scenarios. The two days differ in that one is defined as a work day while the other is defined as vacation day.

Using the above characteristics, here are two different but somewhat similar scenarios, with different context that may help illustrate the need for context. In both scenarios, let us assume that our user travels alone for the whole day, leaves home in the morning and returns in the afternoon.

Let us say now that our traveler is married with two little kids, likes country music, likes nature, outdoor sports, including water sports and especially surfing and likes Italian food and coffee. In the following scenarios we highlight the context-aware personalization service provided by the system in form of recommendations.

1. Working day: Traveling from home to a city nearby for a business meeting. The meeting is planned to start at 10:00, end at 12:00 and our traveler is expected back in the office at 14:30 for another meeting
2. Vacation day: Traveling from home to the same city for a vacation day. During that day our traveler will go to the lake, spend some time there and return home sometime afternoon after enjoying preferred water sport and lunch.

The driving distance from home to the other city is about an hour, depends upon traffic conditions. There is a selection of roads – highways and secondary scenic routes.

In the first scenario, the traveler has a meeting at 10:00, since driving time is about an hour a recommendation for traveling is to **leave home at 08:30** (after rush hour), allowing some time for traffic congestions and planning to arrive a bit early. The travel context is that the traveler travels alone, the time is morning, the season is summer, weather is nice, means of transportation is a private car, travel goal is work, and travel time is about an hour. This traveling context requires information and recommendations about the road conditions, traffic and parking place at the end (parking place, next to the meeting place, where the traveler will get receipt for parking). During the trip, there is another recommendation task: music selection out of a choice of radio stations and CD player. Our traveler drives on the **highway**, listening to a favorite **country** singer, gets to the meeting place about 15 minutes early, parks in a short walking distance from the meeting place. There are 15 minutes to wait, so the system recommends a third task: **having coffee** at a nearby bar. The meeting finishes at 12:30. As our traveler needs to get back to the office by 14:30, the system suggests having a **Pizza** for lunch (fast Italian food) at a near by Pizza stand (also within the expenses budget of our traveler). Our traveler starts driving back to work at 13:30, at this time the system suggest **taking the highway** (shortest path). Regarding music, the system recommends **favorite, but not re-**

laxing (relaxing music may make the traveler sleepy) country music from one of the local radio stations.

In the second scenario, there are no time constraints, so the system suggests **leaving at 09:00** to avoid traffic, taking a **scenic road** to the lake (the city is near a lake), parking in a free parking area, a bit away from the city, but where surfing equipment can be rented and where there are also some restaurants. During the trip to the lake, the system suggests a favored **country** CD. Our traveler gets to the lake, surfs, swims a little and breaks for lunch at 13:00. The system recommends an Italian **restaurant** near the beach. Our traveler decides not to accept the recommendation. Instead he/she decides to start heading home. The system recommends **taking a scenic road** back and stopping in a good Italian **restaurant** along the way, about 15 minutes drive from the lake. Our traveler follows the recommendation. After lunch, the system recommends **favorite but not relaxing** (relaxing music may make the traveler sleepy) country music from one of the local radio stations.

The above two scenarios, detailed for the same users in two different contexts: leisure and work, almost identical in most of the details, demonstrate the idea of context-awareness. Work context is different from leisure context (in this specific example, due different time and budget constraints), and the recommendations are also different. Even within the same general context (work-day context for instance) there are different sub-contexts. For example, restaurant recommendation may be different given the availability of time: if the meeting ended early, there is more time to get to a restaurant, but if the meeting ended late, there is time to grab a Pizza at the nearest Pizza stand and go back to the office.

4 Data Representation

The fundamental problem related to data representation is "how can this heterogeneous situational information be represented in a uniform, efficient and semantically-enriched fashion"? We addressed it basing our approach on so-called *situational statements* [**Error! Reference source not found.**] that serve as integrating data structures for user modeling and context-awareness.

The basic idea behind situational statements is to apply predefined meta-level information in an extended RDF representation with OWL ontologies. These ontologies provide a shared and common understanding of a domain allowing communication between heterogeneous widely spread application systems. The newly defined general UM ontology GUMO [**Error! Reference source not found.**] is collecting the user's dimensions modeled within user-adaptive systems, e.g., the user's age, and occupation. Furthermore, it also facilitates representing the user's interests and preferences.

Similarly, GUMO facilitates modeling in RDF various dimensions of context, e.g., day time, season, companions, motivation (for the traveling scenario) and others. Figure 2 illustrates partial representation of context in GUMO. In the same manner, also the items can be modeled in RDF.

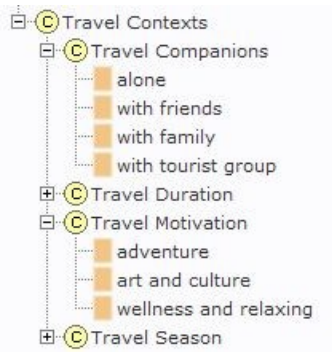


Figure 2: Context Representation in GUMO

5 Reasoning Rules

In the previous section we have seen how we can syntactically represent the data from user models in RDF. As we have explained in the introduction, our interest in this paper is to infer essential parts of a context-aware UMs or provide context-aware reasoning. It means that we are interested in combining context-specific user data and infer context-aware user data.

To explain this inference mechanism, we need to consider the UM data in more detail. A user experience was previously defined as the combination of user feedback for a certain content item in a certain context. For this context to be captured, we use (here in a simplified syntax) situational descriptions, such as:

```
context.motivation=work or
context.time=afternoon
```

With the aid of all the situational statements that we have at our disposal, we should understand what the relevant contextual aspects are. For example, in an experience we will have a combination of a situation, an item, and a rating. Here, we give the details of a concrete example:

```
context.motivation=work
context.time=afternoon
item.meal.price=moderate
rating=0.8 (*)
```

For the moment, we have assumed that these experiences are simply registered and explicitly stored like that. As we have explained in the motivation, it can be the case that we need a UM that deals with the context-awareness in a more efficient way by "inferring the essential parts". Likewise, from the perspective of the personalization system, we can have a case, where a number of experiences are available, but in a new situation no experiences are available to base the recommendation on. To help resolving this problem of inferring the essential parts, we can exploit the inference mechanisms in the data structures. For this, it might be necessary to define rules that indicate how the different aspects of the situations relate to each other. We now sketch a number of illustrative cases, with rules that help to define how we obtain the (cross-context) inferred knowledge.

In the first scenario is we derive knowledge about a more generic situation from a more specific one by discarding some contextual information. For example, a rule:

```
context.motivation and context.time
implies context.time
```

could help to aggregate the detailed knowledge with a certain knowledge referring to `context.motivation` into more coarse-grained knowledge referring to `context.time` only. This could define the factors that are

more important for the context-awareness and help to deal with a situation such as

```
context.time=afternoon
```

by inferring that for this situation, the above rating (*) can be used as a basis for recommendation. Rules like this would help to define how the different contextual aspects are related to each other, such that also for a situation

```
context.motivation=leisure
context.time=afternoon
```

some user modeling information will be available, even if no previously experiences have been recorded for this situation. Note that if there would have been experiences recorded for this situation, applying the above rule would result in multiple ratings being available for consideration in the personalization stage.

In the previous scenario, we have dealt with rules that concern the presence or absence of aspects in the situational statements. In the following scenario, we exploit knowledge about the domain of values for our situation aspects. For example, consider a situation:

```
context.motivation=work
context.time=4pm
```

Knowing the rating (*), we would be able to use this, if we would know that 4pm is a time in the afternoon. So, with a rule like:

```
4pm implies afternoon
```

we would be in the position to keep in the UM only the essential statements for the experiences, and still be able to infer the relevant situations. This scenario fits perfectly with our RDF/OWL-based approach where we can rely on the fact that the value domains are represented through ontological structures that facilitate this kind of inference.

So, the first type of rules is associated with the presence of situation aspects (the genericity of the situations), whereas the second type is associated with the structure inside the domains and domain knowledge for the situational descriptors. Needless to say that it is also possible to define rules that combine the above two types.

As a result of these rules, whenever we are in a situation *S* for which we want to provide personalization, we can infer all those experiences that "hold", i.e. are considered relevant (because they have a situation implying *S*).

We would like to stress that in previous inferences we considered the situation and item parts of the experiences, and not the ratings. Obviously, we could also include the ratings in the rules and exploit them by the inference mechanisms. For example, consider two experiences:

```
context.motivation=work
context.time=afternoon
item.meal.price=moderate
rating=0.8
```

and

```
context.motivation=leisure
context.time=afternoon
item.meal.price=moderate
rating=0.2
```

Availability of ratings in the experiences allows supporting different kinds of reasoning. For example, if the value of `context.motivation` is unknown, some probabilistic model can produce a prediction of:

```
context.time=afternoon
item.meal.price=moderate
rating=0.6
```

We would like to stress that the above examples all relate to one and the same user and item in different situations, i.e., new situations on the basis of situations from previous experiences on the same items. Mainly, the rules help to define how we can infer knowledge based on how the situations are structured. This is therefore an example of pure cross-context reasoning.

We point out here that in the above examples, we did not refer to the item in question (e.g., meal). It is obvious that in the same line we could also have included the items from the experiences in the rules, yielding cross-context item-item reasoning from past experiences on other items in other contexts. In the same spirit, including the users in the rules yields cross-context collaborative (cross-user) reasoning from past experiences of other users in other contexts. Finally, both of the above methods could be integrated, yielding a hybrid reasoning. At this stage, we just point out these possibilities, without exploring them in depth.

Once the required UM data is inferred, the following stage of the context-aware personalization actually deals with generating the recommendations. For this purpose, any state-of-the-art recommendation technique may be applied.

6 Conclusions and Future Research

This paper motivates the need for cross context personalization and suggest an initial model for it. It also integrates it with the ideas adapted from the state-of-the art personalization techniques in order to provide a complete framework for context-aware personalization. Future research will focus on formalizing the model, integrating it with known representation and reasoning techniques and demonstrating it in everyday scenarios as an initial proof of concept.

References

- [Adomavicius et al., 2005] Adomavicius, G., Sankaranarayanan, R., Sen, S., and Tuzhilin, A. (2005). Incorporating Contextual Information in Recommender Systems Using a Multidimensional Approach. In: ACM Transactions on Information Systems, vol. 23, (1).
- [Cinotti et al., 2004] Cinotti T.S., Garzotto, F., Muzii, R., Malavasi, M., Galasso, S., Raffa, G., Roffia, L. and Varlese, V. (2004). Evaluating Context-aware Mobile Applications in Museums: Experiences from the MUSE Project. In: Proceedings of the Eighth Annual Conference on Museums and the Web (MW 2004).
- [Davies et al., 2001] Davies, N., Cheverst, K., Mitchell, K., Efrat, A. (2001). Using and determining location in a context-sensitive tour guide. In: IEEE Computer Society Press 34(8).
- [Kuwahara et al., 2003] Kuwahara, N., Noma, H., Kogure, K., Hagita, N., Tetsutani, N., Iseki, H. (2003). Wearable auto-event-recording of medical nursing. In: Proceedings of the Ninth IFIP TC13 International Conference on Human-Computer Interaction (INTERACT 2003).
- [Harvel et al., 2004] Harvel, L., Liu, L., Abowd, G.D., Lim, Y.X., Scheibe, C., Chatham, C. (2004). Context Cube: Flexible and Effective Manipulation of Sensed Context Data. In: Proceedings of the 2nd International Conference on Pervasive Computing.
- [Heckmann, 2005] Heckmann, D. (2005). Ubiquitous User Modeling. PhD thesis, Department of Computer Science, Saarland University, Germany.
- [Herlocker et al., 1999] Herlocker J.L., Konstan, J.A., Borchers, A., and Riedl, J. (1999). An Algorithmic Framework for Performing Collaborative Filtering, In: proceedings of the SIGIR Conference.
- [Herlocker and Konstan, 2001] Herlocker, J. L. and Konstan, J. A. (2001). Content-independent, task-focused recommendations. IEEE Internet Computing, vol.5.
- [Kern et al., 2006] Kern, N., Schmidt, A., and Schiele, B. (2006). Context Annotation for A Live Life Recording. In: Journal of Personal and Ubiquitous Computing - Special Issue on Memory and Sharing of Experiences, vol. 10, Springer.
- [Kobsa, 2001] Kobsa, A.. (2001). Generic User Modeling Systems. In: User Modeling and User-Adapted Interaction, vol. 11(1-2).
- [Mehta et al., 2005] Mehta, B., Niederée, C., Stewart, A., Degemmis, M., Lops, P., and Semeraro, G. (2005). Ontologically-enriched unified user modeling for cross-system personalization. In Proceeding of the User Modeling.
- [Morita and Shinoda, 1994] Morita, M., and Shinoda, Y. (1994). Information Filtering Based on User Behavior Analysis and Best Match Retrieval. In: proceedings of the SIGIR Conference.
- [Ricci et al., 2003] Ricci, F., Venturini, A., Cavada, D., Mirzadeh, N., Blaas, D., and Nones, M. (2003). Product recommendation with interactive query management and twofold similarity. In: proceedings of ICCBR 2003, the 5th International Conference on Case-Based Reasoning.
- [Wasinger et al., 2003] Wasinger, R., Oliver, D., Heckmann, D., Braun, B., Brandherm, B., and Stahl, C. (2003). Adapting Spoken and Visual Output for a Pedestrian Navigation System, based on given Situational Statements. In: proceedings of the GI-Workshop on Adaptivity and User Modeling in Interactive Software Systems.